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OPTIMAL PLACEMENT OF DG USING EVOLUTIONARY ALGORITHM

UNNATI MALI & PRIYANKA PATEL

Department of Electrical Engineering, CGPIT/UTU, Gujarat, India

ABSTRACT

The increase in power demand and limitation of transmission capacities have led to strong concern among electrical power industrials. The large deployment of distributed generation (DG) sources in distribution network can be an efficient solution to overcome power system technical problems and economical challenges. Unlike centralized electrical generation, the DGs generate electrical energy near to the load centres with small generating capacity. Installing DG may influence power system stability and losses. To maximize such benefits, the optimal locations of DGs are very important. This paper presents artificial intelligent technique to identify optimal DG location while minimization of real power loss. Evolutionary algorithms known as Genetic Algorithm (GA) are opted in solving the optimization problem. The applicability of proposed method is verified using the IEEE 16-bus, 33-bus and 69-bus distribution network.

KEYWORDS: Backward/Forward Sweep Method, Optimal Placement of DG, Genetic Algorithm

1. INTRODUCTION

To satisfy the increasing power demand, huge power plants have to be constructed. However, the intention of building new power plants face with many challenges such as finding a proper place for establishment, costs incurred due to the transfer of the electricity from distant power plants and technical impairments due to long travelling distance of electricity over the transmission lines. The continuous growth in power demand, lack in active power generation as well as limitations of traditional power system structure have led to increased interest in DG utilisation. Distributed generators can be strategically placed in power systems for improving system reliability and efficiency such as improving voltage profiles and reducing power losses [1,2]. The DG resources are normally deployed at distribution networks which are closer to consumption centres. The units are relatively small in size and also modular in structure. Two major aspects, namely the location and sizing of distributed generators strictly require careful attention in the unit's deployment. A common strategy to find the location of DG is to assess the power losses parameter in the system [3,4].

In many parts of the world, the number of DG units being installed in power systems shows an increasing trend. As the installed capacity of DG units increase, it becomes important to study the effects of these sources on electrical systems. Among the major effects include voltage violations and grid losses [5,6]. The voltage profile is directly a function of load consumption while network losses are a function of power flow. The presence of DG has changed the flow of power from unidirectional to bidirectional.

In the modernization of power system industry, distributed generation sources are inevitably becomes important source of electricity supplies. Traditionally, in power system distribution networks only have a single source upstream with loads connected downstream. But in smart grid there is more than one source of generation which can directly transmit electricity to the load. The interest in Distributed Energy Resources (DERs) in smart grid is due to the increased

liberalization of the market, increased interest in the renewable sources of energy, enhanced information and communication technology (ICT) etc. DERs include distributed generations (DGs) and distributed storage devices. The presence of DGs will impact the operation of the grid. With regard to the distribution grid, the DGs are capable of positively as well as negatively impacting it depending on their location, so Optimal Placement of DGs must be done. The installation of DG units at non-optimal places can results in an increase in system losses, implying in an increase in costs and, therefore, having an effect opposite to the desired. The presence DGs calls for the modification in the problem formulation.

The definition of distributed generation (DG) takes different forms in different markets and countries and is defined differently by different agencies. International Energy Agency (IEA) defines distributed generation as generating plant serving a customer on-site or providing support to a distribution network, connected to the grid at distribution-level voltages. CIGRE defines DG as the generation, which has the following characteristics: It is not centrally planned; It is not centrally dispatched at present; It is usually connected to the distribution network; It is smaller than 50-100 MW. Other organizations like Electric Power Research Institute (EPRI) defines distributed generation as generation from a few kilowatts up to 50MW. In general, DG means small scale generation. The most general and simplest definition of DG is as follows: "Distributed Generation is an electric power source connected directly to the distribution network or on the customer site of the meter"[7].

Distributed generations (DGs) are grid-connected or stand-alone electric generation units located within the distribution system at or near the end user. Recent development in DG technologies such as wind, solar, geothermal, fuel cells, hydrogen, ocean and biomass energy has drawn an attention for utilities to accommodate DG units in their systems. As the penetration of distributed generation is expected to increase significantly in the near future, a paradigm shift in control, operation and planning of distribution networks may be necessary if this generation is to be integrated in a cost-effective manner.

Distributed Generations (DGs) play an important role in the minimization loss of the system. DG is considered as “taking power to the load” by both conventional and renewable energy resources. DG generates electricity with high efficiency and low pollution. DGs are closer to the costumers so transmission and distribution cost of electricity and power loss also has been reduced. DG also reduced maintenance and operation cost of transmission and distribution line. In order to minimize line losses of power system, it is important to define the size and location of DG. For optimal placement of DGs also artificial intelligent techniques are used.

In recent years, many researchers have investigated the loss minimization problem in distribution networks using DG. In March 2011, Zonkoly [8] used PSO technique to find the best solution of the multi-objective problem of placing and sizing of distributed generation (DG) units in distribution system with non-unity power factor considering different types of load models. In September 2010, Feng and Qi [9] presented the analytical approaches for optimal placement of DG with unity power factor in radial system to minimize power losses. In November 2008, Wang and Singh [10] presented an ant colony system algorithm to derive the optimal recloser and DG placement by minimizing a composite reliability index for radial distribution networks. In February 2006, Acharya, Mahat and Mithulananthan [11] proposed an analytical expression to calculate the optimal size and an effective methodology to identify the corresponding optimum location for DG placement for minimizing the total power losses in primary distribution systems. In January 2001, Nara, Hayashi, Ikeda and Ashizawa [12] illustrated an implementation of tabu search algorithm (TS) for optimal placement problem of

distributed generators (DG) in order to minimize distribution loss at the demand side of the power system, under the conditions that number of DGs and total capacity of DGs are known.

This paper emphasizes the advantage of optimal placement of distributed generation for loss reduction and bus voltage improvement. Section II presents the mathematical formulation of the proposed index. Section III describes the methodology for finding optimum DG placement. Section IV presents the results of the optimization. The application of GA has been applied to determine the optimal location of the switches to minimize the system loss subjected to system constraints. The effectiveness of the methodology has been demonstrated by a practical sized radial distribution system consisting of 16, 33 and 69 buses.

2. PROBLEM STATEMENT

The purpose of optimal placement of DG in power system is to identify the control variables which minimize the system real power loss and bus voltage deviation while satisfying the operating constraints. This goal is achieved by selection of proper bus number which contains DG. There are two objective functions:

1) Minimization of the power losses: Minimization of the real power loss over the feeders is chosen as the first objective for the Grid reconfiguration since reducing the real power loss of the distribution feeders is a main goal in feeder reconfiguration. Minimization of the total real power losses over the feeders can be calculated as:

$$f(x) = \sum_{i=1}^{N_{br}} R_i \, X \, |I_i|^2 \quad -------- (1)$$

$x = [Tie_1, Tie_2, \dots \dots, Tie_{N_{Tie}}]$ for grid reconfiguration problem

$x = [loc_1, loc_2, \dots \dots, loc_{N_{DG}}]$ for optimal placement of DG

Where, R_i and I_i are resistance and actual current of the i^{th} branch, respectively. N_{br} is the number of the branches. X is the control variable vector. Tie_n is the open switch number from n^{th} loop. N_{tie} is the number of tie switches present in radial distribution system. loc_n is the bus number at which DG is placed. N_{DG} is the number of available DGs.

2) Minimization of bus voltage deviation: Bus voltages are one the most significant security and service quality indices, which can be described as:

$$f(x) = max_i|V_i - V_{rate}| \qquad i = 1,2, \dots \dots N_{bus} \quad - (2)$$

where, N_{bus} is total number of the buses. V_i and V_{rate} are the real and rated voltages on the i^{th} bus, respectively.

Constraints of optimal placement of DG problem are:

1) Voltage limits: Bus voltage amplitudes are limited as

$$Vmin \le Vi \le Vmax \quad - (3)$$

where, $Vmin$ and $Vmax$ are the minimum and maximum values of bus voltage amplitudes, respectively.

2) Branch current constraints: $I_b \le I_{b\,max} \quad - (4)$

where, I_b is the current of branch b, and I_{bmax} is the maximum permissible current of branch b.

3. LOAD FLOW

Load flow is used to calculate objective function's value like power loss, bus voltage, and branch and load currents. Conventional NR and Gauss Seidel (GS) methods may become inefficient in the analysis of distribution systems, due to the special features of distribution networks, i.e. radial structure, high R/X ratio and unbalanced loads, etc. These features make the distribution systems power flow computation different and somewhat difficult to analyze as compared to the transmission systems.

Various methods are available to carry out the analysis of balanced and unbalanced radial distribution systems and can be divided into two categories. The first type of methods is utilized by proper modification of existing methods such as NR and GS methods. On the other hand, the second group of methods is based on backward and forward sweep processes using Kirchhoff's laws. Due to its low memory requirements, computational efficiency and robust convergence characteristic, backward and forward sweep based algorithms have gained the most popularity for radial distribution systems load flow analysis. In this study, backward and forward sweep method [13, 14, 15, 16] is used to find out the load flow solution.

3.1 Backward and Forward Sweep Method

Forward backward sweep based power flow algorithms generally take advantage of the radial network topology and consist of forward or backward sweep processes. In this algorithm, forward sweep is mainly the node voltage calculation from sending end to the far end of the feeder and laterals, and the backward sweep is primarily the branch current or power summation from far end to sending end of the feeder and laterals. Forward and backward sweep algorithm employs KVL and KCL to calculate node voltages. The radial system is solved by a straight forward two-step procedure in which branch currents are first computed (backward sweep) and then bus voltages are updated (forward sweep). The forward/backward sweep is used as an iterative means to solve the load flow equations of radial distribution systems.

3.1.1 Backward sweep

The Backward Sweep calculates the current injected into each branch as a function of the end node voltages. It performs a current summation while updating voltages. Bus voltages at the end nodes are initialized for the first iteration. Starting at the end buses, each branch is traversed toward the source bus updating the voltage and calculating the current injected into each bus.

The load current at node/bus i is given as,

$$I_L(i) = \left(\frac{S_i}{V_i}\right)^* \quad -(5)$$

where, S_i is the power load at ith bus.

$$S_i = P_L(i) + Q_L(i)$$

Branch current of branch between j and i node can be given as,

$$I(j,i) = I_L(i) + \sum_{k \in \beta_i} I(i,k) \quad -(6)$$

Voltage at node i,

$$V_i = V_j + I(i,j) * Z(i,j) \quad -(7)$$

where, $Z(i,j)$ is the impedance of branch between i and j nodes.

3.1.2 Forward sweep

These calculated currents in backward sweep are stored and used in the subsequent Forward Sweep calculations. The calculated source voltage is used for mismatch calculation as the termination criteria by comparing it to the specified source voltage. The Forward Sweep calculates node voltages as a function of the currents injected into each bus. The Forward Sweep is a voltage drop calculation with the constraint that the source voltage used is the specified nominal voltage at the beginning of each forward sweep. The voltage is calculated at each bus, beginning at the source bus and traversing out to the end buses using the currents calculated in previous the Backward Sweep.

Voltage at node i,

$$V_i = V_j - I(j,i) * Z(j,i) \quad -(8)$$

3.1.3 Convergence

Convergence is achieved when the magnitude of the voltage mismatch between the calculated source voltage in the Backward Sweep and the specified source voltage is less than or equal to a specified tolerance. The currents of all branches so calculated during the final iteration of the backward sweep are used for calculation of voltage at each node and also for losses.

3.2 Load flow with DG [17]:

There is an extra consideration in load flow because of distributed generations are present. The DG can be operated in three modes: lagging or leading or unity power factor. Under lagging power factor operation, DG produces reactive power for the system and Q is positive. Also Q is negative for leading power factor operation because DG absorbs reactive power from network. The real power at node *i* is decreased by adding DG at that node, which is given as $(P_{Li} - P_{Gi}) \quad -(9)$

P_L is load power and P_G is real power of generator.

The reactive power in per unit for DG at node *i* is given in Eq.(10).

$$Q_{Gi} = \frac{(-1)^{nG} \gamma P_{Li} \sqrt{1 - (PF_G)^2}}{PF_G} \quad -(10)$$

where, nG = 1 for leading power factor operation

= 2 for lagging power factor operation

$$\gamma = \frac{P_{Gi}}{P_{Li}} \quad -(9)$$

The reactive power at node i is $(Q_{Li} - Q_{Gi}) \quad -(10)$

Then S_i contains real and reactive power. The load flow is done for the radial system using equation (5), (6), (7) and (8).

4. GENETIC ALGORITHM

Genetic algorithm is an evolutionary algorithm. In artificial intelligence, an evolutionary algorithm (EA) is a subset of evolutionary computation, a generic population-based metaheuristic optimization algorithm. An EA uses mechanisms inspired by biological evolution: reproduction, mutation, recombination, and selection. Candidate solutions to the optimization problem play the role of individuals in a population, and the fitness function determines the environment within which the solutions "live" (see also cost function). Evolution of the population then takes place after the repeated application of the above operators. Artificial evolution (AE) describes a process involving individual evolutionary algorithms; EAs are individual components that participate in an AE.

GA is a metaheuristic optimization method, that is, it iteratively solves a problem by improving the candidate solution based on certain criteria. It is based on the principle of evolution. Coming from the family of evolutionary algorithms, GA can deal well with non-convex functions. One of the properties of non convex functions is that they have more than one local optimum. GA, being a stochastic optimization method has probabilistic elements incorporated into the algorithm which helps it in escaping from the local optimum and find the global optimum [18].

The major steps involved in a typical GA are initializing the population, crossover, mutation, selection and termination based on the termination criterion. Population are the chromosomes which represents the possible solutions. The flow of how genetic algorithm works which shown in Figure 1. [19]. Crossover and mutation are the two operators involved in GA. By using crossover operation, two parents are combined to form offspring. Mutation operation adds randomness to the population and hence will prevent the search from being caught in local optima. The crossover and the mutation operators can be set in such a way that both exploration and exploitation of the search space is possible.

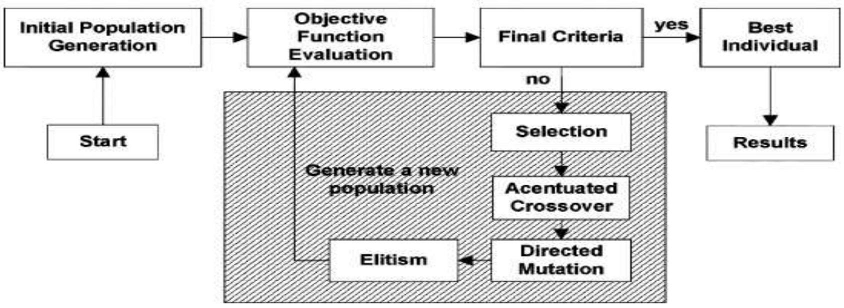


Figure 1: Implemented GA Flowchart

GA was basically designed to work with binary coding, a change in the coding pattern (for example using of real numbers for coding) requires a modification in the way the crossover and the mutation operators are applied on the individuals. Reference [20] uses real and integer coding instead of binary coding. The crossover operator is so chosen that it takes advantage of special structure of the problem representation. Also the mutation operator acts differently on the floating variable and on the integer variable. In this paper for feasible solution of the population real number encoding is used.

4.1 Implementation of Genetic Algorithm for Optimal Placement of DG

There are few steps for implementation of Optimal Placement of DG using genetic algorithm are as follows:

4.1.1 String encoding and initial population of string

String is made up of the location of DG that is bus number. The string length depends on how many number of DGs are available. The string can take any value from 2 to N. N is number of buses present in distribution system. The DG doesn't place only on slack bus that is bus no. 1. For example, 3 DGs are available to place in 16-bus distribution system. Genes (bits) of the individual (string) is between 2 to 16 bus no. So, string may as follow.

DG1	DG2	DG3
14	5	8

Suppose capacity of DG1, DG2 and DG3 are respectively 20 MW, 100 MW and 50 MW. So, 14^{th} bus contains 20 MW , 5^{th} bus contains 100 MW and 8^{th} bus contains 50 MW DG.

4.1.2 Objective Function Evaluation and genetic operators

To calculate with a higher accuracy the power losses, maximum voltage drop and branch current and to make better decisions into the optimization process, the objective functions defined in this work (power loss and Max. Voltage drop) is evaluated using backward forward sweep load flow. also to verify the operational constraints (bus voltage and branch current limit) of the control problem the load flow is used. Most of the CPU time spent by the algorithm is associated with the objective function evaluation and the constraints verification through the load flow. The GA operators are selection, crossover and mutation.

4.1.2.1 Elitism:

After applying GA operators like crossover and mutation, there is a big chance to lose the best solution. So, elitism has been introduced. Elite child is the dominant solution which is directly copy into next generation without applying any GA operators. The chromosome (string) which contains least value of objective function select as the elite child and elite child does not take part in the selection process. In this paper the no. of elite child taken as one for optimal placement of DG.

4.1.2.2 Selection:

Select parents to perform crossover. For selection following methods are available:

1) Roulette wheel selection 2) Tournament selection 3) uniform selection and 4) stochastic selection. For this paper roulette wheel selection has been adopted as it gives better results.

Fitness of each string is sorted in ascending order and then according to that, parents are selected for crossover. How many parents are selected which is depends on the crossover fraction.

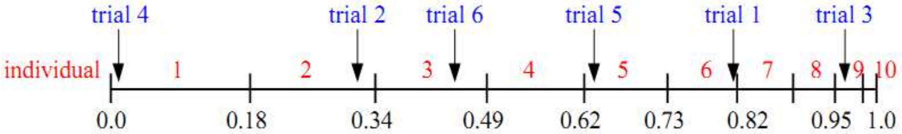
In this paper crossover has been done using roulette wheel method. The roulette wheel selection work as follows [21]:

Suppose 6 individuals have to be selected from 11 individuals using roulette wheel. In Table 1 fitness value of individuals and their probabilities are given.

Table 1: Example for Roulette Wheel

Number of individual	1	2	3	4	5	6	7	8	9	10	11
fitness value	2.0	1.8	1.6	1.4	1.2	1.0	0.8	0.6	0.4	0.2	0.0
selection probability	0.18	0.16	0.15	0.13	0.11	0.09	0.07	0.06	0.03	0.02	0.0

For selecting the mating population the appropriate number of uniformly distributed random numbers (uniform distributed between 0.0 and 1.0) is independently generated. Sample of 6 random numbers: 0.81, 0.32, 0.96, 0.01, 0.65, 0.42.



So, from Table 1 following populations are selected crossover:

1, 2, 3, 4, 6, 8

4.1.2.3 Crossover

This operator aims at mixing up genetic information coming from two different individuals (parents), to make a new individual (child). Crossover is apply only those strings which are selected by any selection method described in above section. The crossover also has many types: 1) Two Point Crossover 2) Single Point Crossover 3) Intermediate Crossover etc. In this project two point crossover has been used. In two-point crossover two random positions are selected. Up to first point the string remain as it is after that point there is change in string up to second point and after this 2nd point string remain as it is. For example, suppose two parents are present for crossover:

Parent 1: 5 11 16

Parent 2: 2 7 3

If point 1 and 2 is select then after applying crossover the generated Childs are:

Child 1: 5 7 16

Child 2: 2 11 3

4.1.2.4 Mutation

Mutations are restricted in one string not like crossover that needs two strings. Mutation is the occasional random alteration of value of string position. For mutation process mutation probability is required. In mutation, random numbers are generated as many as individuals present in the string. Generated random numbers are between 0 to 1. The random numbers which are less then mutation probability have selected and the individuals present at those positions are mutated. The individuals are mutated from their respective places only. So, there are only feasible solutions and no need to check whether the string is feasible or infeasible after performing mutation on it.

For example, String is 5 11 16 and mutation probability (Pm) is 0.34

3 random numbers are generated because 3 individuals are present in the string:

0.93 0.23 0.57

The 2^{nd} number that is 0.23 is less then Pm. So, 2^{nd} position is selected for the mutation and from no. of buses only this individual is altered. If from No. of buses 7 is chosen.

So, after mutation the string is: 5 7 16

4.1.2.5 Termination Criteria

If the elite child that is the best fitness result does not change for a specific number of generations the program is terminated. For this paper, if the elite child doesn't change for 4 generations then the result should be that elite child. If this condition is not satisfied then the process of generating new population with best fitness will be continued until the maximum generation number is reached.

4.2 Algorithm for implementation of Optimal Placement of DG using GA:

Step 1: Read the bus, line data for the distribution test system and data for genetic algorithm such as population size, max generation, crossover fraction, mutation probability.

Step 2: Generate initial population. Each individual in the population is represented by a string which is made up of bus No.

For-LOOP from Step-3 to Step-8

Step 3: Calculate fitness using load flow for each individual in the population.

Step 4: Sort the population - keep the best string (elite child). This process is called elitism.

Step 5: Check constrains (bus voltage limit, branch current limit) after optimal placement of DG. Check termination criteria for convergence. If maximum generation number is reached or if elite child does not change for a specific number of iterations then end the program otherwise go to step 6.

Step 6: Perform Selection using roulette wheel (explain in section 4.1.2.2). Selection of population would be depends on the crossover fraction.

Step 7: Perform two point Crossover on the selected population (explain in section 4.1.2.3).

Step 8: Perform mutation on all population except elite child (explain in section 4.1.2.4).

5. CASE STUDY

Following cases are taken for three different radial distribution systems.

Case 1: Base case

The system is without distributed generation. This case requires only load flow.

Case 2: Optimal Placement of DG

The distribution system same as case 1 with placing DGs at different locations such as objective function should be minimized.

Following are three radial distribution systems to demonstrate effectiveness of the different cases:

16-Bus: The test system is radial distribution system with 16-buses, 13-sectionalizing switches; 3-tie switches (loops). The source voltage is 11 KV and base 100 MVA. The load data are tabulated in appendix [22]. In initial configuration of the distribution system 5,11and 16 are the tie switches and others are the sectionalizing switches. The total loads for this test system are 28.70 MW and 17.30 MVAr.

33-Bus: The test system is 10 MVA, 12.66 KV radial distribution system with 33 buses, 5 tie-lines (looping branches). The load data are tabulated in appendix [23]. The initial statuses of all the sectionalizing switches (switches No. 1-32) are closed while all the tie switches (switch No.33-37) are open. The total loads for this test system are 3,715 kW and 2,300 kVAr. The current carrying capacity of branch No.1-9 is 400 A, and the other remaining branches including the tie lines are 200 A. The minimum and maximum voltages are set at 0.95 and 1.05 p.u, respectively.

69-Bus: The test system is 10 MVA, 12.66 kV radial distribution system with 69 buses, 7 laterals and 5 tie lines (looping branches). The load and branch data of the distribution system are given in appendix [24]. The initial statuses of all sectionalizing switches (switches No. 1-68) are closed while all the tie switches (switch No.69-73) are open. The current carrying capacity of branch No.1-9 is 400 A, No.46-49 and No. 52-64 are 300 A and the other remaining branches including the tie lines are 200 A. The total load of the test system is 3801.89 KW and 2694.10 kVar. Each branch in the system has a sectionalizing switch for reconfiguration purpose.

RESULTS

Table 2: shows different parameters of genetic algorithm.

Table 2: GA Parameters Used for Each System

Test System	Population Size	Crossover Fraction	Mutation Probability	Max. Generations
16-bus	100	0.9	0.05	100
33-bus	100	0.9	0.05	100
69-bus	100	0.9	0.05	100

Table 3: Results of Base Case (before Placement of DG)

Systems	Power Loss(KW)	Max. Voltage Drop (p.u)	Time(sec)
16-bus	536.630	0.0418407	0.053812098909301
33-bus	210.998	0.0969118	0.122520723610369
69-bus	224.958	0.0927932	0.214579826723145

Three DGs are available: 500 KW, 250 KW and 250 KW

Table 4: Results of Case-2 (Optimal Placement of DG)

System	Power Loss (KW)	Loss Reduction (%)	Optimal Location of DGs	Max. Voltage Drop (p.u)	Time (sec)
16-bus	498.627	7.09	11, 12, 16	0.0399352	11.63410370
33-bus	110.380	47.68	31, 14, 13	0.0591202	30.13045983
69-bus	185.522	17.53	11, 13, 23	0.0870052	100.5658575

6. CONCLUSIONS

In this paper the results of application of Genetic algorithm to the optimal allocation of DGs in radial distribution network is presented. Introduction of DGs at proper location reduces more system loss and voltage drop then without DG. Allocation of DGs at non-optimal places leads to some of the power system issues such as high power loss, reduced voltage profile etc.

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